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Reduction potential of CO_2 emissions in China's transport industry

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A B S T R A C T

Energy saving and carbon dioxide emission reduction in China is drawing increasing attention worldwide. China is currently in the stage of industrialization and urbanization, which is characterized by rapid growth of energy consumption. China's transport industry is highly energy-consuming and highly polluting. In 2010, oil consumption in China's transport industry was 38.2% of the country's total oil demand, and accordingly had given rise to increasing amounts of carbon dioxide emissions. This paper explores the main factors affecting carbon dioxide emissions using the Kaya identity. Co-integration method is developed to examine the long-run relationship between carbon dioxide emissions and affecting factors of GDP, urbanization rate, energy intensity and carbon intensity in the transport industry. Both carbon dioxide emission and reduction potential are estimated under different emission-reduction scenarios. Monte Carlo simulation is further used for risk analysis. Results show that under BAU (Business As Usual) scenario, carbon dioxide emission in China's transport industry will reach 1024.24 million tons (Mt) in 2020; while its reduction potential will be 304.59 Mt and 422.99 Mt under moderate emission-reduction scenario and advanced emission-reduction scenario, respectively. Considering this huge potential, policy suggestions are provided to reduce the level of CO_2 emissions in China's transport industry.

Contents

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1. Introduction

1.1. Climate change and the transport industry

Climate change and global warming have attracted increasing attentions worldwide, and has become a serious challenge for many countries. Among various environment challenges, carbon dioxide emission is particularly of great concerned. In 2010, China's carbon dioxide emissions were estimated to be 8332.5 Mt (Million ton), accounting for 25.1% of the world's total emissions [23]. Therefore, world carbon emission mitigation requires commitments from China to control and reduce its emissions from all sources, especially fossil energy. Otherwise, world carbon dioxide emissions are expected to increase at an even higher rate due to China's progress of industrialization and urbanization. Therefore, understanding and analyzing carbon emission factors in China's key industries are of vital importance [32].

The transport industry is an important sector, and is key to national economic and social development. Modern transportation has evolved into an important economic activity for human civilization [31]. The transportation sector is one of the major components of globalization and makes a vital contribution to the economy as well as, plays a crucial role in daily activities around the world [36]. However, given that, the global energy consumption of the transport sectors, is about one third of the total energy consumption of the world at present, energy saving and emission reduction in the transport sector, is of great importance [56]. The transport sector has been identified as one of the major contributors to the depletion of fossil fuels, the degradation of the environment and deterioration of human health [3]. A recent study regarding the influence of anthropogenic activities towards climate change had also proven that the transportation sector would be the highest potential contributor to atmospheric warming in the near decades [31]. At present, fossil fuels take nearly 80% of the primary energy consumed in the world, of which up to 58% alone are consumed by the transport sector [46]. Globally, the transportation sector is the second largest energy consuming sector after the industrial sector and accounts for 30% of the world's total delivered energy [8].

1.2. China's transport industry

China's transport sectors are mainly divided into four parts, which are, road, railway, waterway and civil aviation. In general, China's road transport occupies an important position for middle-short distance transport, and the railway plays a crucial role for long-distance transport [56]. The road transport and railway undertake most of the passenger transport; while the waterway transport and civil aviation only undertake a small amount of traffic volume, but play significant roles in China's international transport. From Fig. 1, it is noticed that road transport has replaced railway and became the dominant passenger transport since 1990. Though the proportion of civil aviation in passenger transport is limited, it has grown rapidly, especially in recent years. For the waterway transport in China, it has the least share in passenger transport but the largest share in freight transport.

As is shown in Fig. 2, energy consumption in China's transport industry is increasing rapidly yearly, particularly in road transport sector due to the considerable increment of vehicles. As the demand for private vehicles is still huge in China, it is expected that the energy consumption in road transport sector will keep growing [33].

It is notable that China's current transport industry is of high energy-consuming and heavy-polluting. As a matter of fact, CO_2

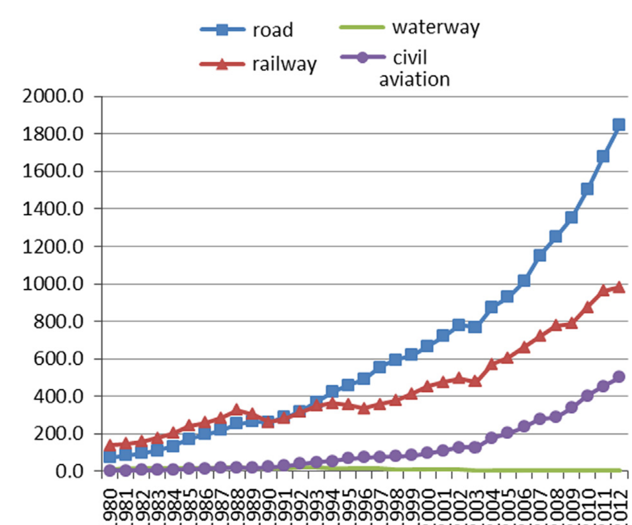

Fig. 1. Turnover volume of passenger transport in China's over 1980–2012 (unit: billion person km).

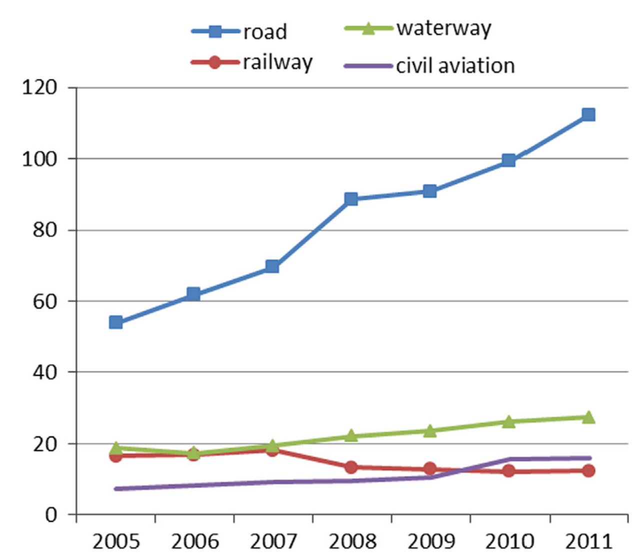

Fig. 2. Energy consumption in China's transport industry over 2005–2011 (unit: MTOE).

emission in China's transport sector was 96.2 Mt in 1990, merely 45% of that of Japan's transport sector of the same year. However, the figure rose to 494.9 Mt in 2010, which was double of that in Japan in the same year. In 2010, oil consumption in the transport sector was 148 MTOE (Million toe of oil equivalents), accounting for 38.2% of China's total oil demand and causing considerable amount of CO_2 emissions accordingly [33]. Furthermore, the absolute amount of energy consumption and the relative proportion of nationwide energy consumption in China's transport sector are increasing obviously yearly [56]. The transport sector, which is a major oil consumer and green-house gas (GHG) emitter, is the most rapidly growing sector in terms of energy demand (especially the oil demand) and GHG emissions in China [34].

1.3. Researches on energy consumption during urbanization process

Currently, many researchers have investigated the connection between urbanization and energy consumption from various perspectives due to the growing concern over the environmental impacts and the energy crises caused by urbanization [55]. Nevertheless, most analyses on the main factors affecting carbon dioxide emissions depend on decomposing of Kaya identity, which cannot effectively explain China's economic reality during the urbanization process. Especially for the factor of population decomposed from Kaya identity, it does not affect carbon dioxide emission as expected when total population is a relatively stable factor due to the family planning policy. However, large scale migration from rural areas to cities during the urbanization process may probably increase energy consumption and carbon dioxide emission, which cannot be reflected through the Kaya identity. Thus, in order to appropriately represent influencing factors to China's transport industry, the original Kaya identity is modified and extended by replacing the factor of total population with urbanization rate in this article, as China's current development characteristics are taken into consideration.

Co-integration is applied and the variable of urbanization rate is introduced into the model, replacing the variable of total population decomposed from the original Kaya identity. Thus, based on both theoretical direction given by Kaya identity and the understanding of influencing factors of carbon dioxide emission during China's urbanization progress, related policy suggestions on low carbon transformation strategy for China's transport industry are provided.

2. Methodology

2.1. Kaya identity

The decomposition of CO_2 emissions into related factors dates back to a series of studies undertaken in the 1980s. Kaya [28] was influential in proposing an identity around which a decomposition of emissions related to four factors could be based:

$$\mathrm{CO_2} \equiv \frac{\mathrm{CO_2}}{\mathrm{E}} * \frac{\mathrm{E}}{\mathrm{GDP}} * \frac{\mathrm{GDP}}{\mathrm{POP}} * \mathrm{POP} \quad (1)$$

where CO_2 indicates CO_2 emissions from energy; E indicates energy consumed; GDP is gross domestic product and POP is population.

CO_2 emission, which is the variable of interest, is related to the product of several factors, and the change in CO_2 emissions cannot simply be expressed as the sum of absolute changes in the four factors. Various solutions to providing a satisfactory and complete decomposition of the changes in emissions, related to the sum of a measure of changes of the factors, have been reviewed by Ang [6] and a widely used solution is based on the so called logarithmic mean Divisia index (LMDI) as explained by Ang [7].

Decomposition analysis on carbon emissions using method of LMDI was carried out by Greening et al. [16–18] and Greening [15] focusing on manufacturing industry, transport industry, residential sector and private transportation sector respectively in 10 countries of OECD. Bhattacharyya and Ussanarassamee [9] analyzed energy and CO_2 intensities in Thai industry with LMDI and found that energy intensity and structural changes are main factors affecting decline. This same method of LMDI was also carried out by Akbostancı et al. [1] in the manufacturing industry of Turkey; Torvanger [52] in the manufacturing industry of nine OECD countries; Reddy and Ray [43] in the manufacturing industries of Indian; Schmitz et al. [47] in the glass industry of European countries; Hammond and Norman [19] in the manufacturing industry of UK; Hatzigeorgiou et al. [20] in Greece; etc.

2.2. Co-integration method

Co-integration method has been proved and introduced by Engle and Granger [13]. Before conducting co-integration analysis, stationary tests are essential for identifying the stationarity of the time series. A stationary linear combination of economic variables indicates the existence of co-integration relationship, which is a long-run equilibrium. The most popular testing procedures for stationarity are Augmented Dickey–Fuller (ADF) tests introduced by Dickey and Fuller [11], Phillips–Perron (PP) tests by Phillips and Perron [40] and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests by Kwiatkowski et al. [30].

The ADF unit root test is based on the following OLS (ordinary least squares) regression:

$$\Delta z_t = \beta_0 + \alpha_0 t + \alpha_1 z_{t-1} + \sum_{i=1}^{m} \beta_i \Delta z_{t-i} + \varepsilon_t \quad (2)$$

where z_t is the variable in period t; Δz_{t-1} is $z_{t-1} - z_{t-2}$; ε_t denotes the i.i.d. (independent identically distributed) disturbance with mean 0 and variance 1; t is the linear time trend and m is the lag order.

The original hypothesis that the unit root occurs in the test of z_t (i.e. $z_t \sim I(1)$) is equivalent to the original hypothesis that $\alpha_1 = 0$ in Eq. (1). If α_1 is significantly less than zero, the original hypothesis of the unit root should be rejected.

The Phillips–Perron test uses the same models as that of the ADF tests, but is remarkably insensitive to the heteroscedasticity and the autocorrelation of the residuals. In this paper, ADF test and PP test are both applied for a comprehensive assessment of the stationary time series.

If the integration of each series is of the same order, then we can further test the existence of co-integration relationship over the sample period. Engle–Granger two-step procedure provided by Engle and Granger [13] and Johansen–Juselius method by Johansen and Juselius [25] and Johansen [26] are the most commonly used methods for co-integration test. Engle–Granger two-step method is applied to a single equation co-integration test, while Johansen–Juselius method can not only detect the existence of co-integration between the variables but also determine the number of co-integration vectors accurately. Therefore, based on the fact that a multitude of variables are used in this paper, we use the Johansen–Juselius method to study the co-integration relationship among the variables.

Co-integration method has been widely adopted to analyze energy demand factors, e.g., modeling energy demand in Mexico [14], Turkey [53], coal demand in India [29], gasoline demand in the United States [37], Fiji [42], India [41], Brazil [4], South Africa [2], and also electricity demand in Sri Lanka [5].

In China, He et al. [21] introduced urbanization into the electricity demand co-integration model, and pointed out that

China's power demand embodied the same features of some developed countries when they were in the process of urbanization. Jiang and Lin [24] analyzed the impacts of industrialization and urbanization on China's energy demand with co-integration model, and concluded that China's energy demand is determined by its particular economic development stage.

2.3. Risk analysis

In this paper, risk analysis model is introduced to verify the co-integration approach. In the co-integration model, future values of variables are predicted based on their historical trends, thereby making the prediction process to be static and merely reflecting one future scenario. Risk analysis can overcome this limitation by means of Monte Carlo simulation. Monte Carlo simulation was first introduced by Metropolis, Ulam [35], relying on repeated random sampling to obtain numerical results. In this study, the risk analysis includes two parts: the possible value of the annual changing rate of each variable in the future and its corresponding possibility. It should be noted that the risk analysis can not only verify whether the co-integration analysis is reasonable or not, but can depict future variation trend in annual percentage rate from the perspective of probability theory. The specific steps in the model are as follows: (A) Determine the probability distribution of annual changing rate of each independent variable according to historical data. (B) Substitute a range of values randomly drawn for annual changing rate of each independent variable according to its own probability distribution. (C) Calculate the future possible value of each independent variable and its probability distribution. (D) Obtain the probability distribution of the dependent variable and depict the probability distribution histograms and cumulative probability curve. This method has been used by Spinney, Watkins [50] as an approach to electric utility integrated resource planning that explicitly identifies key risks imposed on decision makers. Also, it has been used in researching bio-fuel system in France [45], nuclear energy consumption in India [57], and future carbon constrained electricity industries [54].

This paper uses Stata 10.0 to repeat the Monte Carlo simulation process 5000 times.

3. Data resources

From Kaya identity, main influencing factors of carbon dioxide emissions in China's transport industry can be decomposed into carbon intensity and energy intensity in the transport industry, GDP per capital and total population. However, the original Kaya identity is modified and extended by replacing the factor of total population with urbanization rate in this article, as shown by China's current development characteristics. As a result, in order to predict the future carbon dioxide emission and its mitigation potential in the transport industry, indexes of GDP, energy intensity in the transport industry, carbon intensity in the transport industry and urbanization rate are chosen as explanatory variables. The four variables are labeled as GDP, EI, CI and U, respectively.

3.1. Carbon dioxide emissions in China's transport industry (Q)

The CO_2 emission coefficients of different kinds of fossil energies (oil products, coal and gas) are collected from estimations made by the Intergovernmental Panel on Climate Change IPCC (2006), and are assumed to remain the same during the period over 1981–2010. Carbon emissions are calculated by multiplying consumption of individual fossil fuels by their CO_2 emission coefficients. Data on the consumption of different kinds of fuels (oil products, coal, gas and electricity) in China's transport industry over the period 1981–2010 are collected from Asia Pacific Energy Research Centre (APERC).

CO_2 emission of consumed fossil energy in China's transport industry during the period over 1980–2011 are shown in Fig. 3. It shows that the amount of CO_2 emissions in the transport industry in 2011 is almost 10 times of that of 1980, and reducing CO_2 emission in the industry has becomes increasingly emergent today.

3.2. Gross domestic product (GDP)

GDP data for each year are derived from *"Statistical Yearbook of China"* and have been deflated to the constant price in 1979. Fig. 4 shows that GDP and GDP per capita maintained a high degree of consistency in variation over 1980–2012. GDP reflects the level of economic development, people's quality of life and some other comprehensive development levels to a large extent. Thus it also influences the levels of car ownership, car trips, etc., and consequently the energy consumption and carbon dioxide emission in the transport industry.

3.3. Energy intensity in China's transport industry (EI)

Energy intensity measures the amount of energy consumption per unit output of an industry, and is usually influenced by variables such as technology, labor productivity and price of energy. It is formulated as $EI = TE/Y$, where TE indicates total energy and Y indicates output of the transport industry.

Transport industry is one of the service industries. In this sense, the output of the transport industry is "transport service". Transport industry seeks to satisfy passengers' need or to increase the value of cargos, and its only product is the service. In order to measure the output of the transport industry, we have to calculate

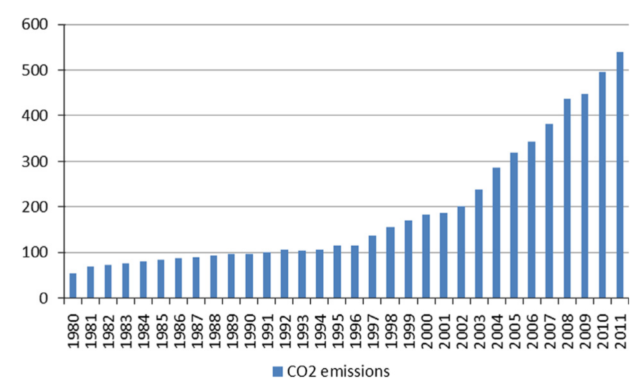

Fig. 3. CO_2 emissions in China's transport industry over 1980–2011 (unit: Mt).

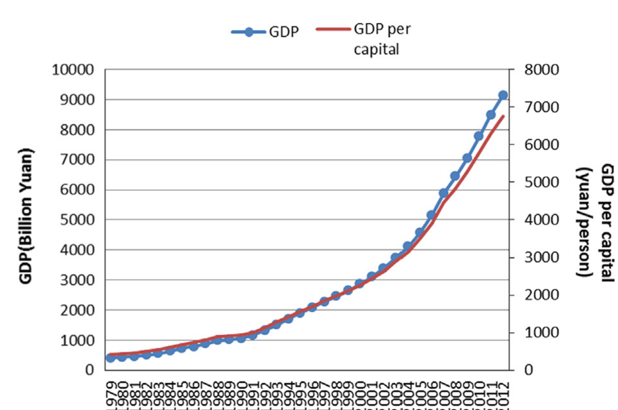

Fig. 4. China's GDP and GDP per capital over 1980–2012.

the total utility it brings to the service objects. Thus, the index of "traffic turnover volume" is chosen, which equals to traffic volume multiplied by load distance. It reflects the quantity of service provided by all kinds of transportation methods. Turnover volume of passenger and turnover volume of cargos are the two indexes reflecting traffic turnover volume in current transportation statistics. However, they are normally incomparable. Therefore, turnover volume of passengers and turnover volume of cargos should be converted into the same measurement, which is defined as 'comprehensive turnover volume' in this paper. The comprehensive turnover volume is obtained by converting turnover volume of passengers into turnover volume of cargos according to a certain scale and then adding them together. It is regarded as a suitable indicator of output of transportation industry, reflecting total turnover volume of both passenger and cargo achieved by all kinds of transportation methods. The computational formula is comprehensive turnover volume = turnover volume of cargos + (turnover volume of passengers * converting ratio of passengers to cargos). The converting ratio value of passengers to cargos is determined by the comparison between manpower and material resources needed to transport 1 t cargo per kilometer and one passenger per kilometer. According to the current statistical system of China, converting ratios of passengers to cargos of railway, ocean waterway, inshore waterway, and inland waterway are 1 for bunk; while converting ratios of passengers to cargos of inland waterway, highway, aviation domestic, and aviation international are 0.3, 0.1, 0.072 and 0.075 for seat, respectively. This is the common method used by domestic researchers at present (such as [58,48]). However, it is not a general approach worldwide, considering the great difference in statistical calibers compared to foreign countries (for more details on Chinese and foreign transport statistical indicators please refer to [51]). Based on converting ratio given by statistical system of China, the turnover volume of passengers and turnover volume of cargos are converted into one standard output indicator of the transport industry in this research, which is the comprehensive turnover volume (Y). Data on turnover volume of passengers and turnover volume of cargos of each sector of the transport industry during the period over 1980–2011 are collected from *China Statistical Yearbook* and *China Transportation Yearbook*.

Limited by statistical caliber, we can only find the data for index of "energy consumption in transportation, postage and storage industry" in China's official statistical yearbooks, from which the amount of total energy consumption in the transport industry cannot be separated. As a result, the data of total energy consumption (unit: kilotons of oil equivalent, hereinafter referred to as KTOE) in the transport industry of China from 1980 to 2011 provided by Asia Pacific Energy Research Centre (APERC) is used instead (labeled as TE for the sake of briefness).

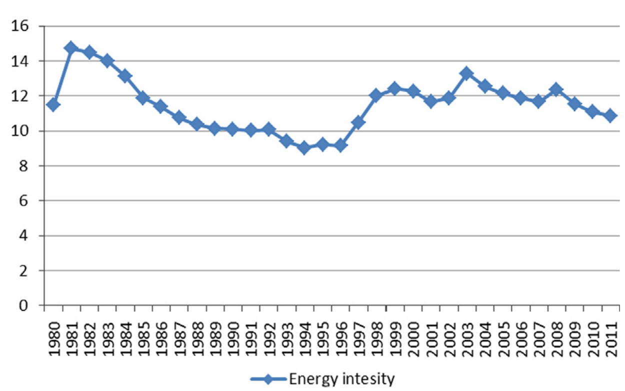

Fig. 5. Energy intensity of China's transport industry over 1980–2011 (unit: TOE/Mt km).

Thus energy intensity of China's transport industry over 1980–2011 is obtained and is shown in Fig. 5.

3.4. Carbon intensity in China's transport industry (CI)

Carbon intensity measures the amount of CO_2 emissions emitted by energy consumed in an industry, representing the quality of energy consumed by this specific industry. It is formulated as $CI = CO_2/TE$. In many countries, such as the United State and Japan, data on carbon intensity are obtained and provided by official organizations. Since there is no any official statistics on carbon intensity of China's transport industry, we have to calculate it according to its expression as in Fig. 6.

3.5. Urbanization rate (U)

Data of China's urbanization rate during the period over 1980–2012 are collected from *China Statistical Yearbooks* and it is shown in Fig. 7. From Fig. 7 we notice that though China's total population increased at a slow and steady growth rate during the last 30 years because of the family planning policy carried out by Chinese government, its urbanization rate increased rapidly. Given China's current development stage and situation, it is preferable to choose urbanization rate instead of total population as an influencing factor to the CO_2 emission in the transport industry.

4. Model results

4.1. Unit root tests

To overcome the shortcomings of the small sample, both ADF unit root test and PP unit root test are used in this paper. Table 1 shows the results of the unit-root tests of all the five variables in terms of both their levels and difference forms.

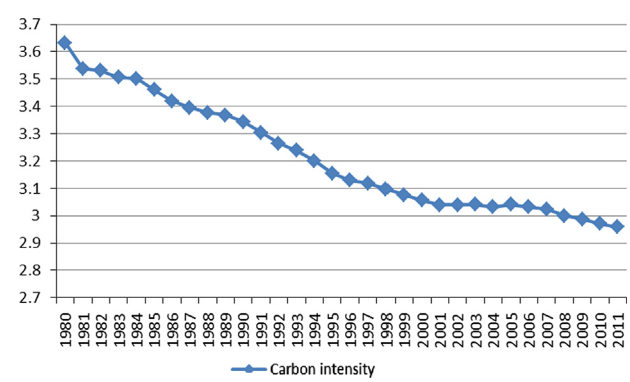

Fig. 6. Carbon intensity of China's transport industry over 1980–2011 (unit: ton CO_2/TOE).

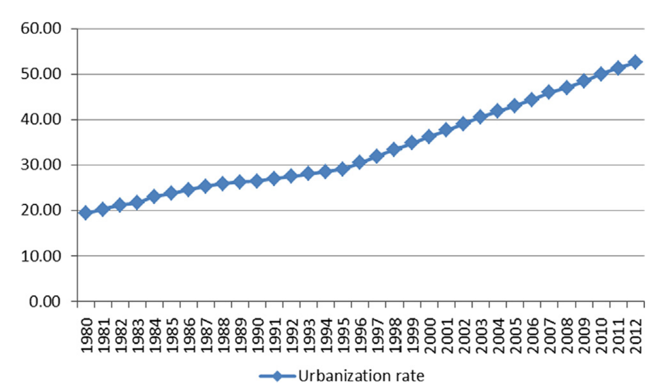

Fig. 7. China's urbanization rate over 1980–2012 (unit: %).

As is shown in Table 1, both ADF test and PP test indicate that all these five variables are first-difference stationary and then we proceed to test for co-integration.

Stata 10.0 is used for the Johansen co-integration rank test, which can indicate the number of linearly independent co-integrate vectors. Results of rank test are shown in Table 2.

Table 1
Unit root tests.

Series	ADF		PP	
	No trend	With trend	No trend	With trend
LnQ	2.571202	−0.632394	2.334218	−0.711597
LnGDP	0.257572	−4.574258***	−0.207812	−2.275505
LnEI	−2.032104	−2.532880	−2.101405	−2.022419
LnCI	−1.897727	−1.061647	−1.601893	−0.531077
LnU	0.484887	−3.592737*	−0.024809	−1.621568
ΔLnQ	−3.446332**	−4.304458**	−3.415727**	−4.248835**
Δ LnGDP	−4.193692***	−4.102019**	−3.112627**	−3.069517*
ΔLnEI	−3.404934**	−3.474407*	−3.426937**	−3.510013*
ΔLnCI	−2.999733**	−3.499375*	−2.996232**	−3.441031*
ΔLnU	−3.508936**	−3.497065	−3.599674**	−3.505643*

Critical values for ADF statistics are given by MacKinnon (1996), those for PP are from [40].

* Indicant at significance level of 10%.
** Indicant at significance level of 5%.
*** Indicant at significance level of 1%.

4.2. Johansen–Juselius co-integration rank test

Unrestricted co-integration rank test of trace (including constant term and temporal trend) rejects the null hypothesis of "rank of co-integration is 0" at 5% confidence level (119.5953 > 77.74) and suggests that there are three linearly independent co-integrate vectors (as starred in Table 2). Unrestricted co-integration rank test of maximum eigenvalue also rejects the null hypothesis of "rank of co-integration is 0" at 5% significance level (54.7583 > 36.41) but it cannot reject the null hypothesis of "rank of co-integration is 1" (27.7696 < 30.33).

In order to continue the co-integration analysis, a VAR model of LLnQ, LnGDP, LnEI, LnCI, LnU was established. Lag intervals of this corresponding VAR representation are tested as in Table 3.

Table 4
Johansen co-integration test.

1 Cointegrating Equation(s):
Log likelihood: 271.1562
Normalized cointegrating coefficients (standard error in parentheses)

LnQ	C	LnGDP	LnEI	LnCI	LnU
1.000000	18.77347	−1.118792	−0.299707	−8.603656	−0.585176
	(0.02150)	(0.00422)	(0.00307)	(0.01227)	(0.01194)

Table 2
Johansen tests for co-integration.

Trend: trend
Number of obs = 28
Sample: 1983–2010
Lags = 2

Maximum rank	Parms	LL	Eigenvalue	Trace statistic	5% critical value
0	35	388.74612		119.5953	77.74
1	44	416.12529	0.85853	64.8369	54.64
2	51	430.01008	0.62908	37.0673	34.55
3	56	441.85895	0.57102	13.3696*	18.17
4	59	447.67021	0.33972	1.7471	3.74
5	60	448.54375	0.06049		
Maximum rank	parms	LL	Eigenvalue	Max statistic	5% critical value
0	35	388.74612		54.7583	36.41
1	44	416.12529	0.85853	27.7696	30.33
2	51	430.01008	0.62908	23.6977	23.78
3	56	441.85895	0.57102	11.6225	16.87
4	59	447.67021	0.33972	1.7471	3.74
5	60	448.54375	0.06049		

* The corresponding number of linearly independent co-integrate vectors.

Table 3
Selection order criteria.

Sample: 1985–2010
Number of obs = 26

Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	202.251				1.8e−13	−15.1732	−15.1035	−14.9312
1	387.962	371.42	25	0.000	7.9e−19	−27.5356	−27.1175	−26.0839
2	420.247	64.568	25	0.000	5.7e−19	−28.0959	−27.3295	−25.4345
3	462.891	85.289	25	0.000	3.1e−19	−29.4532	−28.3384	−25.5821
4	587.725	249.67*	25	0.000	1.2e−21*	−37.1327*	−35.6696*	−32.0519*

Endogenous: lnq lngdp lnei lnci lnu.
Exogenous: _cons.

* The corresponding lag interval chosen by each criteria of LL, LR, FPE, AIC, HQIC and SBIC.

4.3. Selection of lag intervals for VAR model

As is shown in Table 3, lag intervals for the VAR representation are conformably chosen according to all the criteria of LogL, LR, FPE (Final Prediction Error), AIC, HQIC and SBIC (as starred in Table 3), which are 4. Based on these results of Johansen co-integration test is obtained as presented in Table 4.

4.4. Co-integration model results

Corresponding equation can be obtained according to these normalized cointegrating coefficients listed in Table 4 (standard error in parentheses):

$$\begin{aligned} LnQ = &-18.77347 + 1.118792{*}LnGDP + 0.299707{*}LnEI \\ &+ 8.603656{*}LnCI + 0.585176{*}LnU \end{aligned} \quad (3)$$

Several conclusions can be drawn from the standardized equation (3).

First, the above co-integration equation suggests that there is a long-run relationship among these five variables over the period 1981–2010.

Second, the results show that the coefficients of LnGDP, LnEI, LnCI, and LnU are all positive, which are consistent with our estimation and in accordance with the social economic reality.

Third, as GDP and urbanization rate grows, the enhanced living standard and urbanization process may probably lead to more energy consumption and carbon dioxide emission in the transport industry. Elasticity coefficient suggests that 1% increment of GDP and urbanization rate will respectively lead to 1.12% and 0.59% increment of carbon dioxide emission in the transport industry.

Fourth, lowering the energy intensity and carbon intensity in the transport industry can positively reduce carbon dioxide emission in the transport industry in the long run. In effect, this model is assumed to be reasonable, because it is consistent with the expectations based on relevant economic theory.

As a comparison, we also call the command of "reg" in Stata 10.0 and obtain a long-run equilibrium equation based on OLS estimation:

$$\begin{aligned} LnQ = &-26.29424 + 1.450046{*}LnGDP + 0.8569005{*}LnEI \\ &+ 12.28397{*}LnCI + 0.0958445{*}LnU \end{aligned} \quad (4)$$

Table 5
Eigenvalue stability condition.

Eigenvalue	Modulus
1	1
1	1
1	1
1	1
0.8462624 +0.365935i	0.921992
0.8462624 −0.365935i	0.921992
0.107462 +0.9069836i	0.913328
0.107462 −0.9069836i	0.913328
−0.5983726 +0.5819202i	0.834674
−0.5983726 −0.5819202i	0.834674
0.1413935 +0.7661629i	0.779101
0.1413935 −0.7661629i	0.779101
0.5749504 +0.5133084i	0.770749
0.5749504 −0.5133084i	0.770749
0.7193484	0.719348
−0.6387484 +0.04690509i	0.640468
−0.6387484 −0.04690509i	0.640468
−0.03807972 +0.3698898i	0.371845
−0.03807972 −0.3698898i	0.371845
0.0129793	0.012979

The VECM specification imposes 4 unit moduli.

We find that there are certain differences between the estimated values of coefficients of the OLS method and that of the co-integration method. However, all signs of the coefficients obtained by these two methods are the same. According to Chen [10], theoretically estimations given by Johansen co-integration are more effective.

Stability of the co-integration model is tested, as shown in Table 5.

4.5. Stability test

Stability test shows that, except these unit roots assumed by VECM model itself, all the eigenvalues of adjoint matrix are smaller than 1, which means that there is not any characteristic root outside of unit circle and this model satisfies stability condition.

4.6. CUSUM test

Once the co-integration relationship is determined and the parameters are estimated, it is imperative to test for robustness of the model. As a result, the CUSUM (cumulative sum) test is applied to test the constancy of the coefficients in the model. After the error correction model has been built, the Pesaran and Pesaran test [39] is used to calculate the cumulative sum of recursive residuals (CUSUM) in order to examine the parameter stability. From Fig. 8 we notice that the model is qualified stable, as the plots of CUSUM statistics are confined within the 5% critical bounds of parameter stability.

4.7. Model fitting accuracy

In order to verify the forecast function of the model, historical data of GDP, EI, CI and U over 1981–2010 are substituted into co-integration equation (3) and thus the fitted values of carbon dioxide emission in China's transport industry during the last 30 years are obtained and described in Fig. 9. We compare the fitted value with actual value of carbon dioxide emission in China's transport industry and find that the fitting accuracy is rather high; as a result, this model can be used for forecast.

5. Risk analysis

Future carbon dioxide emission in China's transport industry can be predicted by co-integration equation. For this reason,

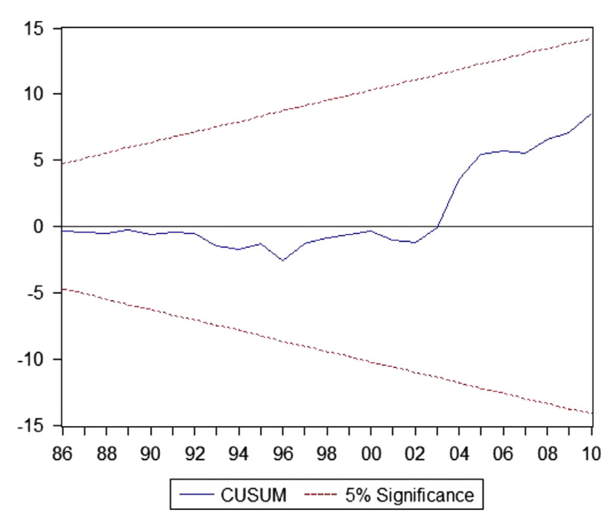

Fig. 8. CUSUM test for stability.

tendency of variables in the right side of the co-integration equation (3) has to be discussed first.

Fig. 10 reflects the changing tendency of China's gross domestic product (GDP), urbanization rate (U), energy intensity in the transport industry (EI) and carbon intensity in the transport industry (CI). We set the annual average growth rates of these variables over 1981–2010 as a baseline scenario (which is the Business As Usual scenario), based on the historical trend observed for each variable. In other words, under BAU condition, each variable will still maintain this annual average growth rate over 2011–2020, and thus future carbon dioxide emission in China's transport industry can be predicted. For the carbon dioxide reduction potential, we considered the BAU scenario as a base line for policy actions.

Under baseline scenario (BAU), annual average growth rates of China's gross domestic product (GDP), urbanization rate (U), energy intensity in the transport industry (EI) and carbon intensity in the transport industry (CI) are 9.88%, 3.18%, −0.97% and −0.60%, respectively. Our time interval of forecast is 2013–2020, as it is a critical period for China's economic transition and this prediction can provide a reference to related policies on CO_2 emission reduction in China's transport industry.

Based on the annual average growth rates of all independent variables above as well as co-integration equation (3), carbon dioxide emission in China's transport industry in 2015 and 2020 are predicted, which are 712 Mt and 1024 Mt, respectively.

The above prediction shown in Fig. 11 is based on the set annual growth rate of each independent variable. However, the growth rate of each independent variable for each year is uncertain. There can be plenty of probabilities for their growth rates each year; and as a result, more reasonable prediction should be a

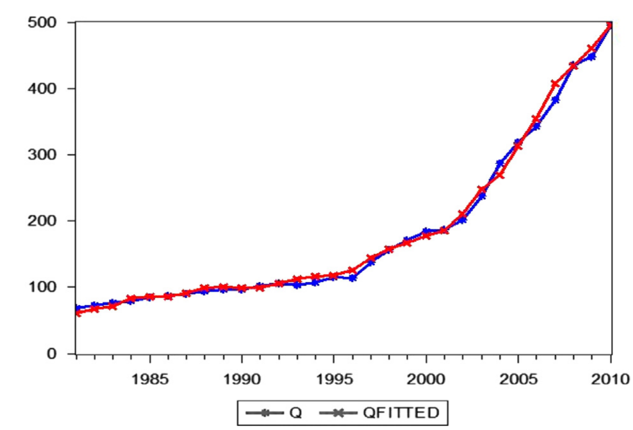

Fig. 9. Plots of actual and fitted values for energy consumption (unit: Mt).

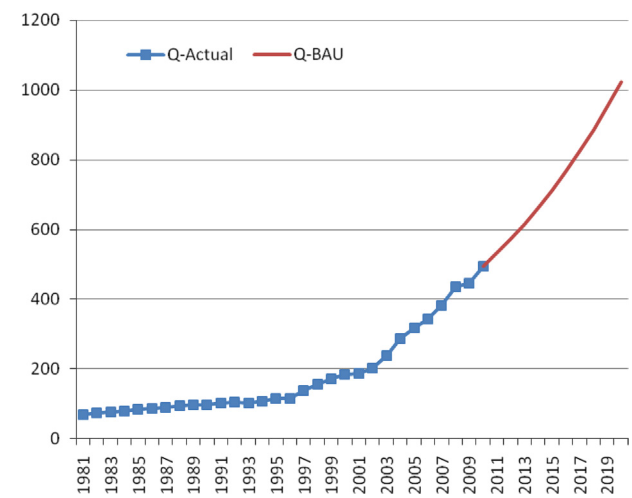

Fig. 11. Prediction on carbon dioxide emission in China's transport industry (unit: Kt).

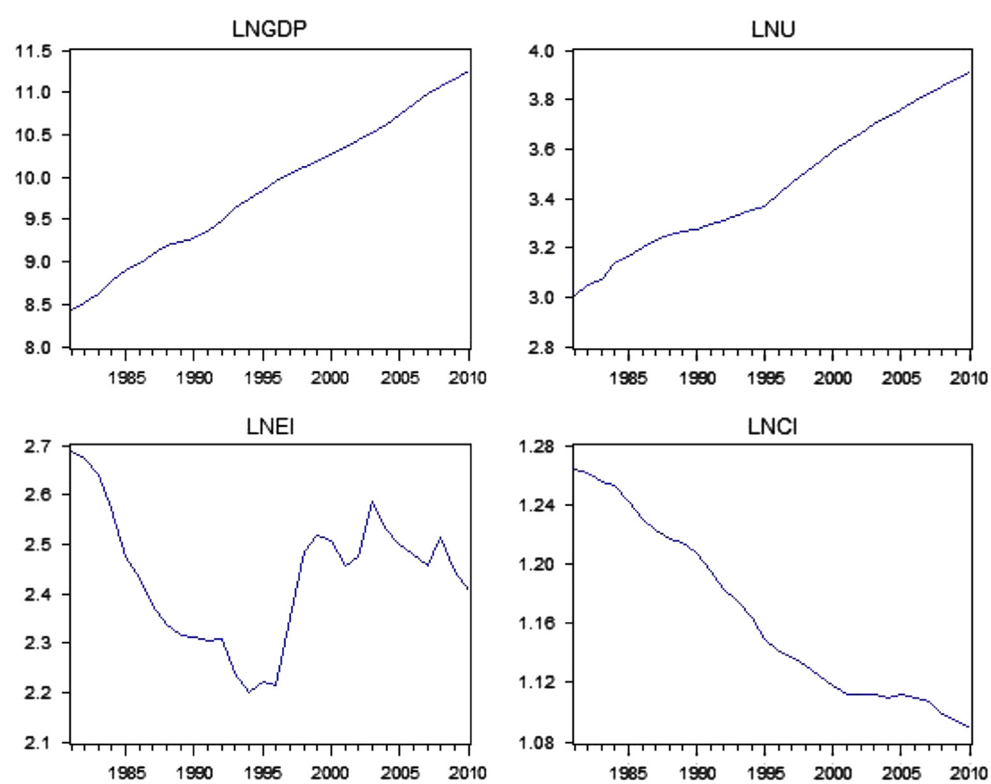

Fig. 10. Tendency charts of independent variables (1982–2010).

set of results and their corresponding probabilities. Therefore, we focus on most likely carbon dioxide emissions and their corresponding probability of the transport industry in 2020 by using risk analysis.

Key procedure of Monte Carlo is random sampling according to distribution of each variable. From experience, most economic variables are normally distributed. Matlab 7.0 is applied for distribution test of growth rate of each independent variable during the last 29 years. Results suggest that they are all normally distributed under confidence level of $\alpha=0.05$. After confirming they are approximately normally distributed, we call "sum" demand in Stata 10.0, and thus the mean values as well as the standard deviation of the annual growth rate of each independent variable are obtained. In Table 6, d. LNGDP means difference between $LNGDP_t$ and $LNGDP_{t-1}$, indicating annual growth rate of GDP of year t (this growth rate can be negative).

Thus, normal distribution of annual growth rate of each independent variable can be obtained based on its own mean value and standard deviation, as listed in Table 6. And then we use random numbers generated by Monte Carlo simulation according to their own distribution as annual growth rate of each explanatory variable. Thus, value of explained variable (carbon dioxide emission in China's transport industry) in 2020 can be calculated according to these random numbers. Repeating this procedure 5000 times, there will be 5000 groups of random numbers generated and consequently 5000 probable values for the explained variable in 2020, obtaining the probability distribution of carbon dioxide emission in China's transport industry in 2020.

Distribution histogram as well as cumulative probability curve of carbon dioxide emission in China's transport industry in 2020 is obtained and described in Figs. 12 and 13 on the basis of Monte Carlo simulation.

As shown in Fig. 12, probability of [950, 1050] Mt will be the maximal interval for carbon dioxide emission in China's transport industry in 2020. CO_2 emission in China's transport industry in 2020 will be 1024 Mt according to the prediction above under BAU condition, which lies right in the interval of [950, 1050] Mt, demonstrating the rationality of our prediction.

Table 6
Statistical property of each independent variable.

Variable	Obs	Mean	Std. Dev.	Min	Max
d. LNGDP	29	0.0974188	0.0247243	0.0376711	0.1412916
d. LNEI	29	−0.009741	0.0580906	−0.0988123	0.1371865
d. LNCI	29	−0.0054963	0.0038106	−0.0138479	−0.0003228
d. LNU	29	0.0312927	0.0120821	0.0075808	0.0623307

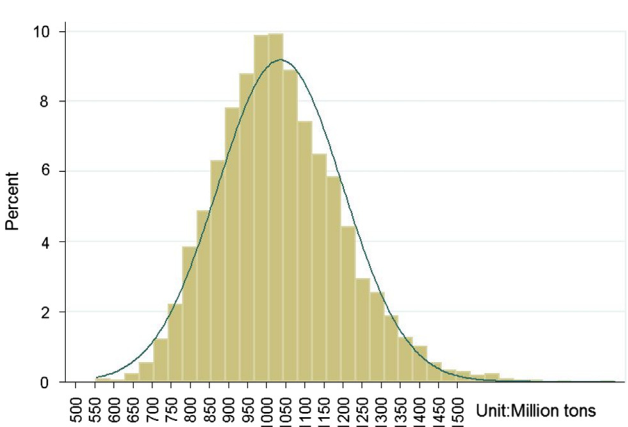

Fig. 12. Distribution histogram of carbon dioxide emission in China's transport industry in 2020 (unit: Mt).

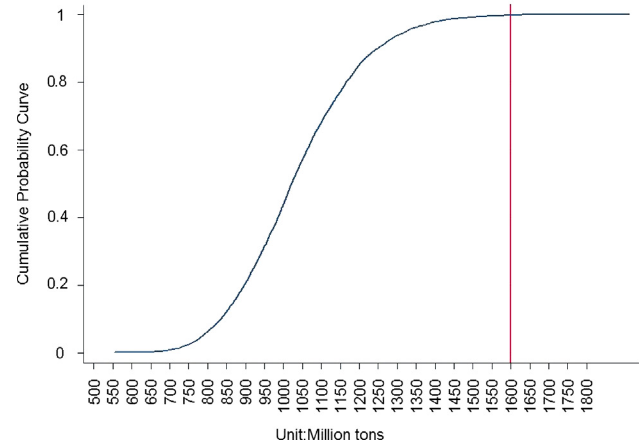

Fig. 13. Cumulative probability curve of carbon dioxide emission in China's transport industry in 2020.

From Fig. 13, it is clear that if the growing trend of each affecting factor of carbon dioxide emission in China's transport industry is maintained, the probability that CO_2 emission in China's transport industry in 2020 will be less than 1600 Mt is approximately 100%; while the probability that CO_2 emission in China's transport industry in 2020 will be less than 650 Mt is approximately 0%.

Scenario analysis approach is applied to calculate reduction potential of carbon dioxide emission in China's transport industry under different emission-reduction scenarios.

6. Future CO_2 reduction potential from scenarios

To realize China's emission-reduction goals, targets should be determined based on energy-saving and emission-reduction potential of enterprise or sector. In order to obtain future mitigation potential of carbon dioxide emission in China's transport industry two other different scenarios – the moderate scenario and advanced scenario – are combined with the BAU condition. Similar scenario analysis has been used in researches such as IEA [22], Dowling and Russ [12], Roinioti et al. [44], Parka et al. [38], Kalashnikova et al. [27], Shuklaa and Chaturvedib [49].

Advanced scenario is a situation that under certain policy incentives and the restriction of economic reality, each affecting factor develops in a way leading to the strongest CO_2 emission-reduction effects; while moderate scenario is a rather mild situation based on the current economic developing situation, which can be regarded as a medium situation between the BAU and the advanced scenario. In other word, the advanced scenario represents the most committed scenario to reduce the carbon emission, and the moderate scenario is considered to be the average policy commitment.

As to the annual growth rate of GDP, it is stated that the GDP growth is mapped out at an annual growth rate of 7% in the next five years according to "*China's 12th five-year program for national economic and social development*" announced in 2011. However, compared with the previous development plans and the actual situations of economic development, this projection is rather conservative. For instance, compared with the actual annual GDP growth rate of 9.5%, the proposed development goal of 7% in the tenth "five-year plan" is much lower. The proposed development goal in the eleventh "five-year plan" is 7.5%; while the actual annual GDP growth rate during that period is 9.5%. As China is still

Table 7
Growth rate assumptions under different scenarios.

Variables	BAU (%)	Moderate scenario (%)	Advanced scenario (%)
GDP	9.88	8.00	7.00
EI	−0.97	−1.50	−2.00
CI	−0.60	−0.70	−0.75
U	3.18	2.80	2.50

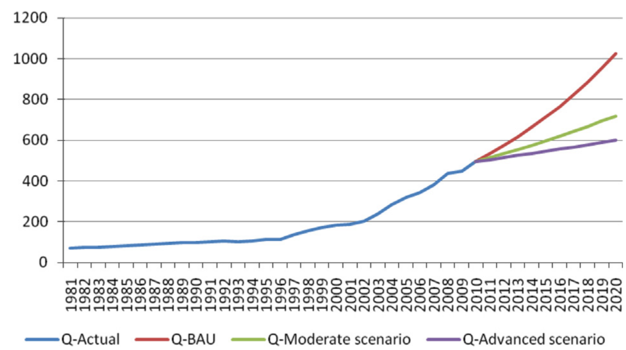

Fig. 14. Forecast on carbon dioxide emission in China's transport industry under different scenarios (unit: Mt).

in a stage of rapid economic growth, we set 7% as the growth rate of GDP under advanced scenario, which indicates strict compliance with the development plan, imposing restriction on energy consumption and slowing down economic growth. Relatively, the growth rate of GDP under moderate scenario is closer to reality, and also between BAU scenario and advanced scenario. Thus 8% GDP growth rate is selected. Similarly, after taking into consideration both the economic constraints and relevant development plans, annual growth rate of energy intensity of the transport industry is set at −1.50% under moderate scenario and −2.00% under advanced scenario; while annual growth rate of carbon intensity of the transport industry is set at −0.70% under moderate scenario and −0.75% under advanced scenario. For annual growth rate of urbanization rate, 2.80% is set under moderate scenario and 2.50% under advanced scenario. The scenario-differentiated growth rates for these independent variables are listed in Table 7.

The scenario-differentiated growth rates for these independent variables are reasonable and realizable, taking into consideration both China's actual national conditions and economic constraints.

Thus carbon dioxide emission in China's transport industry under different scenarios in the future is predicted according to the above mentioned scenario-differentiated growth rates of independent variables and the previous described co-integration equation (3), as is shown in Fig. 14.

Carbon dioxides emission in China's transport industry in 2015 is predicted to be 597.22 Mt under moderate scenario and 545.89 Mt under advanced scenario, which are 16.2% and 23.4% lower than that of BAU scenario, respectively. Carbon dioxides emission in China's transport industry in 2020 is predicted to be 719.65 Mt under moderate scenario and 601.25 Mt under advanced scenario, indicating 29.7% and 41.3% l decreases from the BAU scenario, respectively.

In order to estimate the future reduction potential of CO_2 emission in China's transport industry, two emission-reduction scenarios are set. In moderate emission-reduction scenario, carbon dioxide emission in China's transport industry transforms from baseline scenario (BAU) to moderate scenario. Accordingly, in advanced emission-reduction scenario, carbon dioxide emission in China's transport industry transforms from baseline scenario (BAU) to advanced scenario. According to the prediction of carbon dioxide emission in China's transport industry under different scenarios, reduction potential of CO_2 emission in China's transport industry under the two emission-reduction scenarios is calculated as Table 8.

Table 8
Reduction potential of CO_2 emission in China's transport industry (unit: Mt).

	2015	2020
Moderate emission-reducing scenario	115.26	304.59
Advanced emission-reducing scenario	166.59	422.99

As is shown in Table 8, there is huge reduction potential of carbon dioxide emission in China's transport industry in the future. If carbon dioxide emissions in China's transport industry change from the baseline scenario (BAU) to the moderate scenario (Moderate emission-reduction scenario), the quantity of carbon dioxide reduction will be approximately 115.26 Mt CO_2 by 2015 and 304.59 Mt CO_2 by 2020. If more ambitious measures are implemented, meaning that the CO_2 emissions change from the BAU scenario to the advanced scenario (Advanced emission-reduction scenario), the reduction potential will be higher. It is estimated to be about 166.59 Mt CO_2 by 2015 and 422.99 Mt CO_2 by 2020.

7. Conclusions and suggestions

This paper focuses on the reduction potential of carbon dioxide emission in China's transport industry in the future. For this reason, we consider carbon dioxide emission in the transport industry as the explained variable, and estimate the coefficients of four independent variables including GDP, urbanization (*U*), energy intensity (EI) and carbon intensity (CI) by using annual time series. Co-integration method is developed to investigate the presence of a long-run relationship between carbon dioxide emission and the independent variables. The long-run elasticity of each independent variable to carbon dioxide emission is also obtained. Risk analysis carried out by Monte Carlo simulation verifies the reasonableness of the co-integration model, suggesting that more aggressive emission-reduction policies are needed to narrow mitigation potential of carbon dioxide emission in China's transport industry. Further scenario analysis indicates that, driven by a variety of emission-reduction policies, growth rate of carbon dioxide emission in China's transport industry will become smaller in the future, and the mitigation potential of CO_2 emission will further reduce, thereby resulting in rather considerable reduction amount of CO_2 emission.

Main conclusions of this paper are drawn as follows.

First, there is a long-run relationship among these five variables of *Q*, GDP, EI, CI and U over 1981–2010. Lowering the energy intensity and carbon intensity in the transport industry is conductive for reducing CO_2 emission in China's transport industry as expected.

Second, according to the long-term equilibrium equation (3), carbon intensity is the dominant factor influencing CO_2 emission in the transport industry. Carbon intensity measures the amount of CO_2 emissions emitted by energy consumed in an industry, representing the quality of energy consumed by this specific industry. The change of carbon intensity is due to the alteration of energy consumption structure. GDP growth is the second largest influencing factor of CO_2 emission in the transport industry which is in line with the current economic stage in China – there is a rigid energy demand. High energy elasticity coefficient of GDP explains

that rapid economic growth is another factor causing increment of CO_2 emission besides carbon intensity in the transport industry.

Third, lower energy intensity and carbon intensity both have a positive effect on reducing CO_2 emission reduction in the transport industry in the long run, and carbon intensity has much larger influence on CO_2 emission compared to energy intensity. It provides a theoretical foundation to related reduction policy of carbon dioxide emission in China's transport industry.

According to the conclusions of this paper, emphasis and orientation of emission-reduction policies in China's transport industry in the future can be confirmed, and corresponding measures on CO_2 emissions reduction are given as follows. Along with rapid economic development and urbanization in China, key procedure for CO_2 emission reduction in China's transport industry lies in reducing carbon intensity, which relies on optimization of energy consumption structure. China's transport industry is currently to a large extent dependent on oil. It not only causes concern on energy security problems but also leads to high pollution and emission. The improvement in energy consumption structure can directly inhibit and mitigate carbon dioxide emission in China's transport industry.

Also, results suggest that there is huge reduction potential of carbon dioxide emission in China's transport industry in the future. Under moderate emission-reduction scenario, when carbon dioxide emissions in China's transport industry change from the BAU to the moderate scenario, the quantity of carbon dioxide reduction will be approximately 115.26 Mt CO_2 by 2015 and 304.59 Mt CO_2 by 2020. According to '*2013 EDMC Handbook of Energy & Economic Statistics*', CO_2 emission in China and Japan's transport industries in 2010 was 494.9 Mt and 239.8 Mt, respectively. That means, if relevant policies as mentioned under the moderate emission-reduction scenario are carried out, the total emission reduction of China's transport industry by 2015 will amount to nearly half of the total CO_2 emission of Japan's transport industry in 2010.

Actually, there are obvious differences between China's transport industry and Japan's, especially in energy consumption structure. Oil products are the dominant energy consumed in Japan's transport industry, accounting for a stable percentage of more than 97% in total energy consumption over 1980–2011. For China's transport industry, the proportion of oil products in total energy consumption was merely 30.9% in 1980, and then rose to 87.6% in 2011. Meanwhile, the proportion of coal consumption in total energy consumption decreased sharply, implying optimization of energy consumption structure in China's transport industry, thereby resulting in decrease in carbon intensity. As there is still room for improvement of energy consumption structure, it is believed that huge reduction potential of carbon dioxide emission in China's transport industry exists.

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